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**Wavelet Based Approach to
Transmitter Identification**

by

Ralph D. Hippenstiel

December 1995

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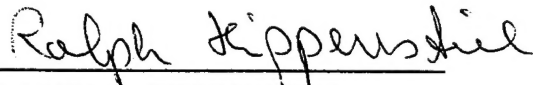# Naval Postgraduate School
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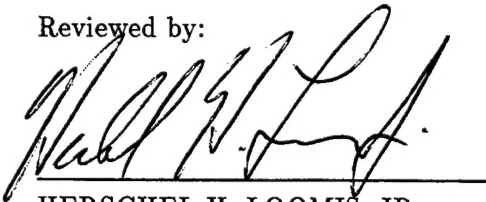
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13. ABSTRACT (Maximum 200 words)

Research is conducted to find a robust wavelet based algorithm for automatic identification of push-to-talk radio transmitters. Digital data at an intermediate frequency (IF) is preprocessed to translate it into a form applicable to wavelet analysis. The magnitudes and the relative positions of the extrema from the best suited wavelet scales are used in conjunction with a distance measure algorithm to determine from which transmitter any particular signal may have originated. The distance measure algorithm can correctly identify the four signal sets provided for the research. Even at reduced signal to noise (SNR) ratios good identification is obtained. The current version of the algorithm can classify all sets, with at least an 80 percent reliability at an SNR on the average 10 dB worse than the original recordings. The procedure lends itself to an automated, minimizing human interaction.

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Executive Summary:

Research is conducted to find a robust wavelet based algorithm for automatic identification of push-to-talk radio transmitters. Digital data at an intermediate frequency (IF) is pre-processed to translate it into a form applicable to wavelet analysis. The magnitudes and the relative positions of the extrema from the best suited wavelet scales are used in conjunction with a distance measure algorithm to determine from which transmitter any particular signal may have originated. The distance measure algorithm can correctly identify the four signal sets provided for the research. Even at reduced signal to noise (SNR) ratios good identification is obtained. Automatic selection of a good (i.e. optimal) threshold, the simultaneous use of several scale outputs and a more robust choice of the reference templates should be addressed in follow on work. The current version of the algorithm can classify all sets, with at least an 80 percent reliability at an SNR on the average 10 dB worse than the original recordings. The procedure lends itself to be automated, minimizing human interaction.

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I.   Introduction

Signals generated by different transmitters are believed to possess somewhat different characteristics. The transient response of a transmitter is defined to be the carrier strength change from the off-state to the on-state, and of course from the on-state to the off-state. The turn on response is unique to a specific transmitter and may even differ among units of the same make and model. These observations are not applicable to the turn-off response. Therefore, the uniqueness of the turn-on transients is exploited to identify the source of the signals and therefore the transmitter.

Time-frequency analysis of stationary signals is a well studied and known subject. The Fourier Transform (FT) method is well suited for this type of analysis. However, when the signal of interest is non-stationary, the FT method is not appropriate, since it uses a complex exponential basis function that exists over infinite time. A sliding time-window (Gaussian) was introduced by Gabor (1946) to gain time information from the FT method. This modified Fourier Transform method is called the Short Time Fourier Transform (STFT). Once a window is chosen, the time-frequency resolution is fixed. This method requires that the signal is stationary within these intervals.

A technique more suitable for transient signal analysis is the Wavelet Transform (WT) method. It is more revealing than the STFT method in terms of time and frequency information. Basis functions of the WT, unlike the complex exponential of the FT, or STFT are shorter in time duration then the analysis interval. This compact support makes the WT localized, in frequency and in time. Moreover, wavelets provide the flexibility to choose the particular wavelet function that is appropriate for a specific application. This is possible since there are a large number of

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compactly supported wavelets that can be used as orthogonal basis functions.

The purpose of this report is to investigate the use of the WT method to classify transmitter signatures.

II. Signal Preprocessing and Filtering.

1. Signal Preprocessing:

Representative data from each source, that is one signal from each transmitter is shown in Figure 1 and 2. Figure 1 displays typical turn on transients, while Figure 2 shows the respective turn off transients. The data is recorded after it is intercepted by the antenna and processed by a typical radio receiver. The carrier frequency of the radio is 138.525 MHz. The signals are filtered with a 1 Mhz bandwidth (BW), digitized at a sampling frequency of 5 Mhz at a center frequency of 1.075 Mhz. The signals are in binary form with 10 bits available for a discrete value representation. These signals (i.e. digital recordings) are pre-processed (i.e. modified) to change the data into a form suitable for WT processing.

There are four steps in the pre-processing phase, sequentially given by:
1) taking the envelope,
2) filtering,
3) differentiating, and
4) a final filtering.

Prior to taking the envelopes, the DC terms are removed. 100-point boxcar averagers are used for filtering the envelope, whereas 50-point boxcar averagers are used after the differentiation. The sizes of the filters were experimentally determined.

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The processing of the turn off transient did not lead to identification, hence our work deals only with the turn on transient portions of the data. Widening the processing band width by using higher sampling rates may allow classification of the transmitters based on turn off characteristics. Of course, a larger bandwidth allows more noise to pass, making this approach less reliable at a given SNR level. The bandwidth (about 2.5 MHz) of the data set may not permit the observation of very short duration transients if they indeed do exist.

(a)

(b)

(c)

(d)
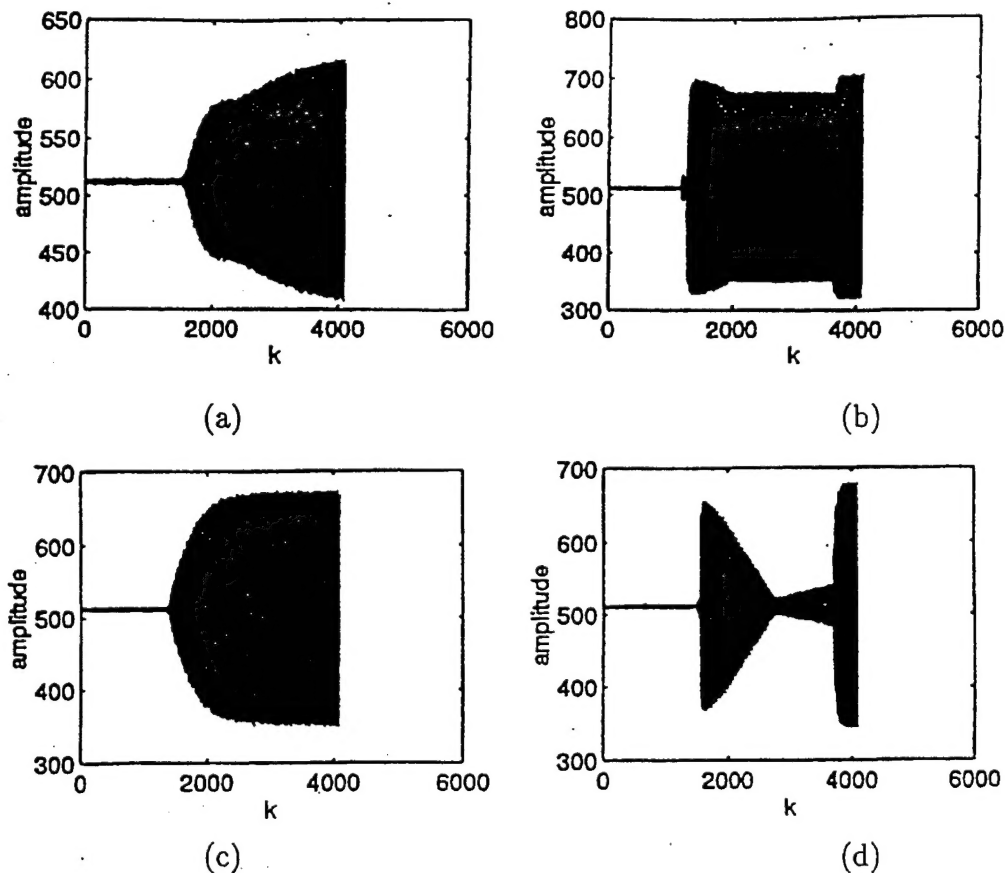
Figure 1. Turn On Transients From Four Transmitters.
Transmitters: (a) = 1, (b) = 2, (c) = 3, (d) = 4 .

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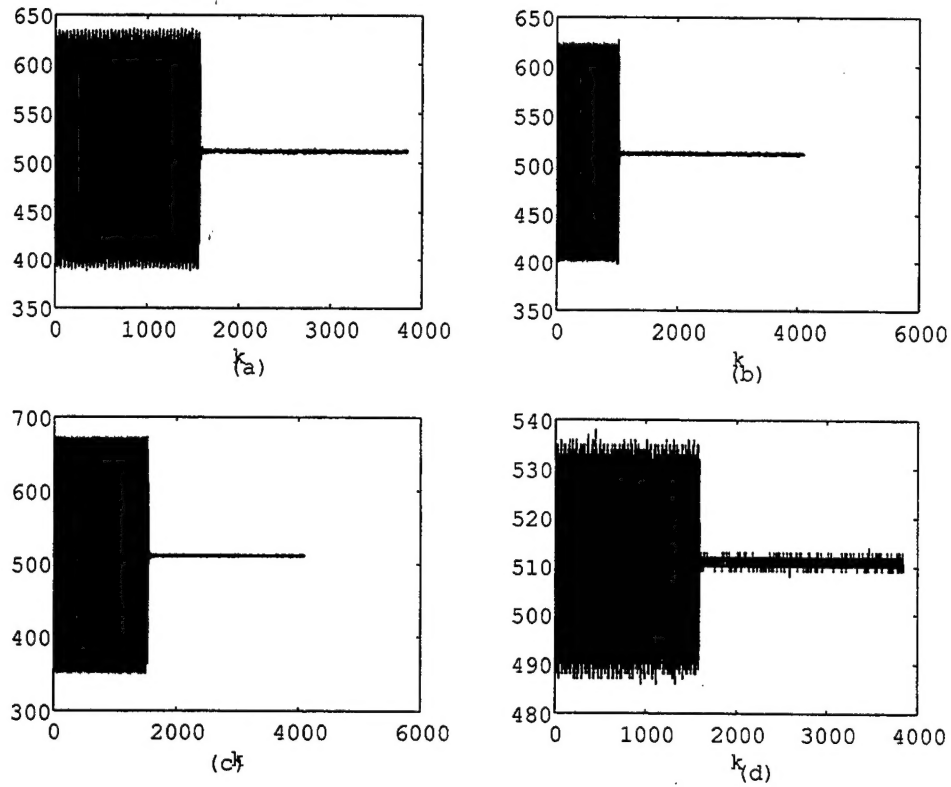
Figure 2. Turn Off Transients From Four Transmitters.
       Transmitters: (a) = 1, (b) = 2, (c) = 3, (d) = 4 .

A closer look at the turn on transients reveals a signal
with a typical ramp type behavior (i.e. unit step response
of a second or higher order linear system). They may differ in
slope, have unique dips or a slow oscillation of the envelope
(i.e. 1 to 2 cycles over the ramp duration). However none of
these transients, even with the DC component removed, is in a
form to which the WT is directly applicable. Wavelet Transforms

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are not useful in analyzing low frequency signals, but they are well-suited for short duration phenomena. Thus, it was necessary to transform the data into a form suitable for wavelet analysis. Details are presented in the next chapter. It should be noted that a denoising process tends to enhance the identification performance.

To transform the envelopes of the signals into a form which allows successful WT analysis, the envelope is differentiated changing the ramps (i.e. step responses) into pulse like signals. Figure 3 shows the typical results after the pre-processing operation when applied to the signals shown in Figure 1. The differentiation is a high pass operation that provides a gain that is linearly proportional to frequency. That means, the high frequency components become emphasized. Unfortunately, this also applies to the additive noise components so that careful filtering must be employed during the stages of the pre-processing. From empirical studies and some theoretical considerations a filtering operation is selected and applied to the data before and after the differentiation.

The data used in the analysis was collected and recorded by the Naval Security Group Activity, Charleston, SC. Nine turn-on/off samples of each of four transmitters were recorded. All the radios are Motorola models. Each radio is identified by its model name and number and is listed below:

Radio:	Model:
Transmitter 1 (Tr1)	Maxtrac
Transmitter 2 (Tr2)	Saber
Transmitter 3 (Tr3)	HT440
Transmitter 4 (Tr4)	Saber.

Tr2 and Tr4 are different radios of the same model.

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Figure 3. Pre-processed Turn On Signals (4 Transmitters)
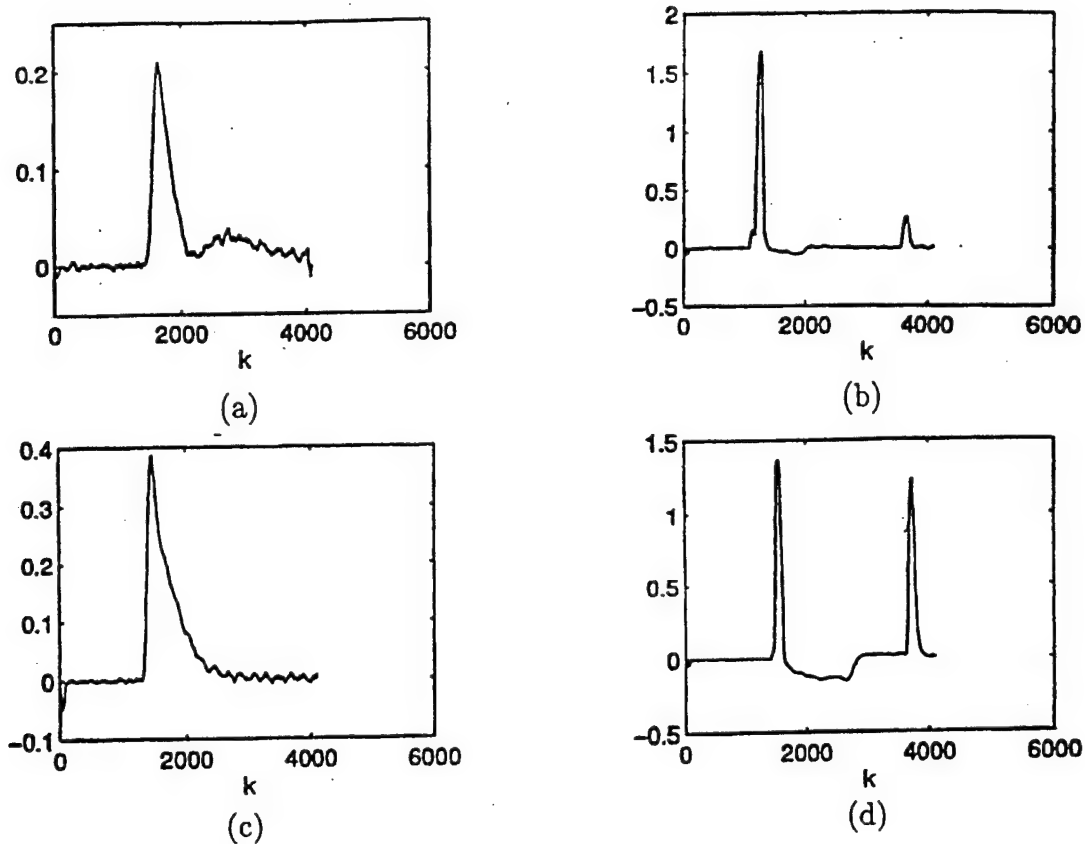Transmitters: (a) = 1, (b) = 2, (c) = 3, (d) = 4 .

2. FILTERS

In the implementation of the pre-processing two filtering operations are performed. The first one follows the envelope

operation and removes some of the broadband noise. This filter (boxcar averager of length 100) is followed by a differentiation operation (i.e. first order difference). The differentiation emphasizes the high frequency noise at the same rate as the first filter tends to attenuate it. Hence a second filter (low pass) operation is implemented. The second filter uses again a box car averager, in this case of length 50. Boxcar averagers are also called integrate - and - dump filters. Sometimes they are referred to as moving average filters. They slide along the time series (the data) and form an average over the length of data span contained within the filter memory. The frequency response of the boxcar averager is a digital sinc function, which is very similar to the familiar analog sinc function. One could incorporate all three operations (lowpass - differentiation - lowpass) into one sophisticated filter, but for ease of computation and efficiency this is not done. Processing that uses median filtering in place of the last lowpass filter in the pre-processing phase is an alternative scheme that can be pursued at some time. This would minimize the spreading due to the convolutional filtering (median filtering tends to preserve the rise and fall times of a pulse).

III.   WAVELET TRANSFORM (WT)

1.   Introduction

Wavelets are proportional bandpass processing schemes which are also known as constant Q-filtering (Akansu and Haddad, 1992; Burrus and Gopinath, 1993). Typical basis functions are the Walsh, Daubechies, spline, and sinc basis function. The Walsh function is a set of rectangular basis function, the Daubechies functions are solutions to the scaling function, the spline

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function uses a triangular scaling coefficients, comparable to a Bartlett weighting in a FIR low pass filter. The sinc function is equivalent to a brick (ideal) low pass filter. The bandpass filter structure uses these basis functions as impulse response in proto-type FIR filters to achieve the proportional band pass filtering.

The Wavelet Transform (WT) is founded on a set of specific basis functions, which are called wavelets (Young, 1993). They include short duration/high frequency and long duration/low frequency functions. Each element in the wavelet set is constructed from the same function, which is called the 'analyzing wavelet' or the 'mother wavelet'.

There are three conditions for a function to be a mother wavelet. It must be oscillatory, it must decay to zero, and it must integrate to zero (Young, 1993).

The processing scheme is adopted from Newland, which requires that the scaling coefficients have to be given to the wavelet transform routine (Pitta, 1995). Since the signals of interest are expected to have a some discontinuity in phase and/or in amplitude, basis functions are selected with matched filtering as motivation.

Several WT were tried with the Daubechies polynomial of order 8 best suited for the data at hand (Payal, 1995). This is understandable in a matched filter sense, if we compare a typical output waveform from the pre-processing procedure with the family of Daubechies polynomials. The processing is accomplished by forming the inner product of the scaling coefficients (i.e. low pass filter) and the wavelet coefficients (i.e. high pass filter) with the data as indicated by equation 3.1:

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$$d_{mn} = < x(t), \psi_{mn}(t) >$$

$$\psi_{mn}(t) = a_0^{-m/2} \psi (a_0^{-m} t - nb_0)$$

$$x(t) = \sum_m \sum_n d_{mn} \psi_{mn}(t)$$

$$\psi(t) = 2 \sum_n d(n) \phi(2t-n)$$

$$\phi(t) = 2 \sum_n c(n) \phi(2t-n)$$

$$d(n) = (-1)^n c(N-n);$$

(3.1)

where $c(n)$ & $d(n)$ are the weights selected for the lowpass & highpass filter, respectively. N is the length of the filters and d_{mn} is the wavelet transform coefficient at scale m and time (delay) n. The $d(n)$ coefficients are the wavelet coefficients which related to the scaling coefficients in a simple manner (i.e. position reversed and alternating in sign). $\Psi(t)$ and $\Phi(t)$ are the wavelet function and scaling function, respectively.

2.   Filter Banks and Discrete Wavelet Transform

Multiresolution analysis can be implemented by using a technique called Multiresolution Pyramid Decomposition or Mallat's algorithm (Vetterli and Kovacevic, 1995). Mallat's Pyramid Algorithm is used to obtain the Discrete Wavelet Transform (DWT). The Discrete Wavelet Transform coefficients at scale j are obtained by convolving the coefficients at scale j+1 with $h_0(n)$ and $h_1(n)$. The impulse responses $h_0(n)$ and $h_1(n)$ are the time reversed coefficients of $c(n)$ and $d(n)$, respectively. This followed by a decimation procedure to produce the expansion coefficients at scale j. Figure 4 shows the implementation of the

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Mallat Pyramid Algorithm for three levels (i.e. scales). The notation LP represents a lowpass FIR filter, while HP represents a highpass FIR filter.
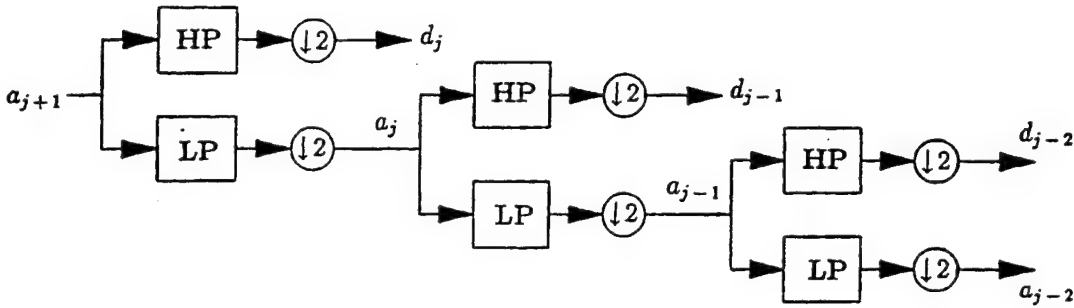

Figure 4.   Three Levels of Multiresolution Analysis

Due to its pipe line structure the algorithm is very fast. It can be faster than an FFT, since the processing cost is linearly proportional to the data length. All filters in a given class (i.e. LP or HP) are identical, making the implementation fairly simple.

IV.   IDENTIFICATION PHASE

1.   Reduced Set Representation

One of the main drawbacks of the discrete (time) wavelet transform is the shift variance, since the wavelet coefficients of a signal and a shifted replica of itself can be very different. A Euclidean distance measure (introduced by Aware,

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Inc., 1992) is used as part of the technique to classify the signals at scales where the effects of shift variance can be tolerated.

Mallat and Zhong (1989) demonstrated that the maxima extracted from the modulus of the wavelet coefficients can be used to reconstruct the input signal. That is, the maxima of the modulus of the wavelet coefficients contain approximately the same amount of information as the original signal. Consequently, signal analysis can be performed based on the wavelet extrema, which form a reduced signal representation.

Thus, wavelet coefficients at each scale are replaced by their extrema. The reduced set is only non zero where the scale has an extrema, and is equal to the original value at these locations. Wavelet scale coefficients, which are not extrema, are set to zero.

2. Ranking/Pairing Algorithm

The first step, in computing a distance measure based on pairing, is to rank the peaks of the sets to be compared. That is, the peaks at each scale are ranked by their amplitudes (i.e. same procedure as is used in median filtering). Therefore the ranked sequences are ordered (ranked) starting with the smallest value and ending with the largest value.

The second step is to pair the ranked peaks of the two sequences to be compared. The peak with the highest rank (largest amplitude) in one set is paired to the peak with the highest rank (largest amplitude) in the other set. The next in rank (order, sequence) is paired to that next in rank of the other set. The pairing scheme does not require the number of elements in both

sets to be the same. When a peak in one set does not have a corresponding peak in the other, a zero is inserted into the set that has a smaller number of peaks, and the pairs are formed by matching the remaining peaks and the zeros.

3. Distance Measure

The third step is to compute a distance measure for the matched pairs. Several distance measures were initially tried. The best results were obtained by using the ranking and pairing technique. It is noted that the ranking approach will be sensitive to the additive noise component. The distance assigned to the pair is the sum over the Euclidean distances in each scale. Thus, we compute

$$d(a^j, b^j) = \sum_{(k,m)} [W^j_{k,m} (a^j_k - b^j_m)^2]^{1/2} \qquad (3.2)$$

where (k,m) denotes the locations of matched peaks, a^j and b^j are the wavelet extrema at scale j, and a^j_k and b^j_m are the values a^j, b^j at temporal locations k and m, respectively. $W^j_{k,m}$ is the weighting factor at scale j for the relative distances between the corresponding coordinates of matched peaks. The weighting factor, $W^j_{k,m}$, is defined as

$$W^j_{k,m} = \begin{cases} |n^j_k - n^j_m| & ; \text{ if } k \neq m \\ 1 & ; \text{ if } k = m \end{cases} \qquad (3.3)$$

where n^j_k and n^j_m are the coordinates of a^j_k and b^j_m, respectively.

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The similarity between two sets is described in terms of the sum of the Euclidean distances of amplitudes weighted by the square root of the relative distances between the corresponding coordinates. Basically, a small value $|n^j_k - n^j_m|$ and $|a^j_k - b^j_m|$, implies a high degree of similarity between a^j and b^j.

The penalty weight, $W^j_{k,m}$, is determined by the separation of the peaks and has a lower bound of unity. Large separation between the matched peaks corresponds to large penalty factors. The distance measure also depends on the amplitude difference of the matched peaks. The distance measure is directly proportional to the difference in amplitude. It should be noted that even identical scale outputs with an offset in time (due to signal delay) would have a non zero weighting factor. This problem is eliminated by removing the offset time prior to forming the distance measure. One can do this by correlating the signals to be identified, with the template and subtracting off the amount of misalignment (i.e. compensate for the amount of lag indicated by the cross correlation). A second way, which was used in the work presented here, is to line up the dominant peaks of the signal of interest and the template in the scale under consideration. This naturally lines up the coefficients (i.e. extrema) in a way that compensates for relative time off set between the two sequences under observation.

4. Implementation

There is a total of four different signal sets. Each set is generated by a different transmitter. The method outlined so far was employed to determine the transmitting source of the signal. For this purpose, a template for each transmitter set is needed to measure the degree of similarity with any signal of interest.

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The distance measure algorithm is applied to a template and a signal of interest at the appropriate wavelet scale after compensation of the time offset.

The first signal from each of the four sets was chosen as a template. A small distance measure implies that the signal under consideration comes from the set that the template represents.

The fourth, eighth, and sixteenth order Daubechies wavelet functions were used to compute the WT of the pre-processed signals. The eighth order Daubechies (Dau-8) wavelet functions gave satisfactory results, whereas Dau-4 and Dau-16 did not. The Dau-8 wavelet function, which was used as the mother wavelet, is shown in Figure 5.
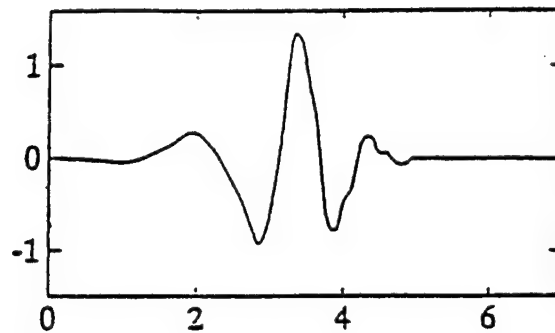

Figure 5.   Eighth Order Daubechies Wavelet Function

For illustration purposes, the distance values at Scale 11 between the first four signals from Transmitter 1 and the templates are tabulated in Table 4.1. As expected, the distance value with Template 1 is significantly less than that with the other templates, since Template 1 is the template for the signals

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from Transmitter 1, and small distance values imply high similarity.

	Templ.1	Templ.2	Templ.3	Templ.4
signal 1	0.00	44.30	14.77	107.84
signal 2	3.05	47.23	16.34	103.85
signal 3	2.61	40.58	13.79	99.78
signal 4	1.08	42.90	15.48	105.30

Table 4.1 Distance Measures 'd' at Scale 11 for Signals 1-4 of Transmitter 1

As can be seen, the distance values 'd' between signals from Transmitter 1 and Template 1 are well separated from those of the other templates. Zero value in distance indicates a perfect match which occurs between Signal 1 and Template 1. This is expected since Signal 1 was chosen as a template for the set. Similar results are obtained when comparing the different signal sets with the four templates [Payal,1995].

A thresholding technique can be introduced to automate the identification procedure by defining a threshold level for each template. For example, one can compare the maximum value of Set 1 with the minimum values of other templates. Determining the threshold levels is not addressed in this study; however, comparing the minimum and maximum values of the distance measure is quite useful in evaluating the performance of the identification scheme. The maximum and minimum values quoted in the remainder of this chapter are obtained by using all template

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and all data sets. At Scale 11 with Template 1, the maximum
distance value is 5.3971, whereas the nearest minimum distance
value of the other three templates is 12.52. This minimum occurs
with Template 3, which indicates that Transmitter 1 and
Transmitter 3 have a somewhat similar transient response (i.e.,
turn-on behavior). The ratio of the minimum Template 3 output to
the maximum Template 1 output is 2.319, which shows how well the
Template 1 results are separated from the other template results.
This separation ratio is 2.381 and 1.66 for Scale 10 and Scale 9,
respectively. Lower scales (lower than 9) were not useful in
terms of the similarity measurement, and are not included.

Similarly, the application of the distance measure to the
other three signal sets resulted in the following separation
ratios. Again these separation values are the ratio of the
smallest wrong set distance and the largest correct set distance.
They show how well the signals of a particular set are separated
from the other sets under worst case conditions. The separation
ratios are 3.56, 2.76, and 1.88 for signals from Transmitter 2 at
Scales 11, 10, and 9, respectively. The following separation
ratios were obtained at Scales 11, 10, and 9: 4.64, 1.98, and
3.73 for signals from Transmitter 3; and 1.75, 1.4, 1.24 for
signals from Transmitter 4. Signal versus template (distance
measure) output plots for all signal sets are given in Appendix
A. One can obtain minima, maxima , and the spread of the distance
measures very easily from the plots. It should be noted that, for
Transmitters 1, 2, and 3, nine signals were used while, for
Transmitter 4, only six signals were usable.

5.   Probability of Identification

Signal-to-Noise Ratios (SNR's) for all signals were
estimated. It is clear from Figure 1 that the signal waveform can

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be partitioned into three regions. The off region is where there is no signal; the transition region is where there is a build-up from off to on state; and the on region is where the signal is at steady state. We can assume that the off region consists of noise only, allowing the computation of the noise power. Noise and signal coexist in the on region. The signal power can be computed by finding the power in the on region and subtracting the noise power. Hence, we can compute the SNR's for all sets. An average SNR value of 32.38 dB, 40.87 dB, 38.58 dB, and 31 dB was computed for Set 1, Set 2, Set 3, and Set 4, respectively.

Gaussian white noise is added to all signal sets to decrease the SNR levels. To obtain some statistical significance the experiments are repeated eleven times for each SNR value, and the probability of identification (P_I) versus SNR is computed. The P_I, the probability of identification is defined as the ratio of the number of correct identification and the total number of experiments.

The results are shown in Figure 6. If the signal of interest is from Transmitter 1 and its SNR is better than 16 dB, then its identification probability is high. The minimum SNR values required for a reliable classification at Scale 11 are 30, 23, and 30 dB for signals from Transmitter 2, 3, and 4, respectively. Several line up (pairing) procedures were tried on an experimental basis, to see if the identification procedure can be made more robust. So far only the distance measure that uses all extrema and pairs the ranked peaks seems to be effective in classifying the four signal sets.
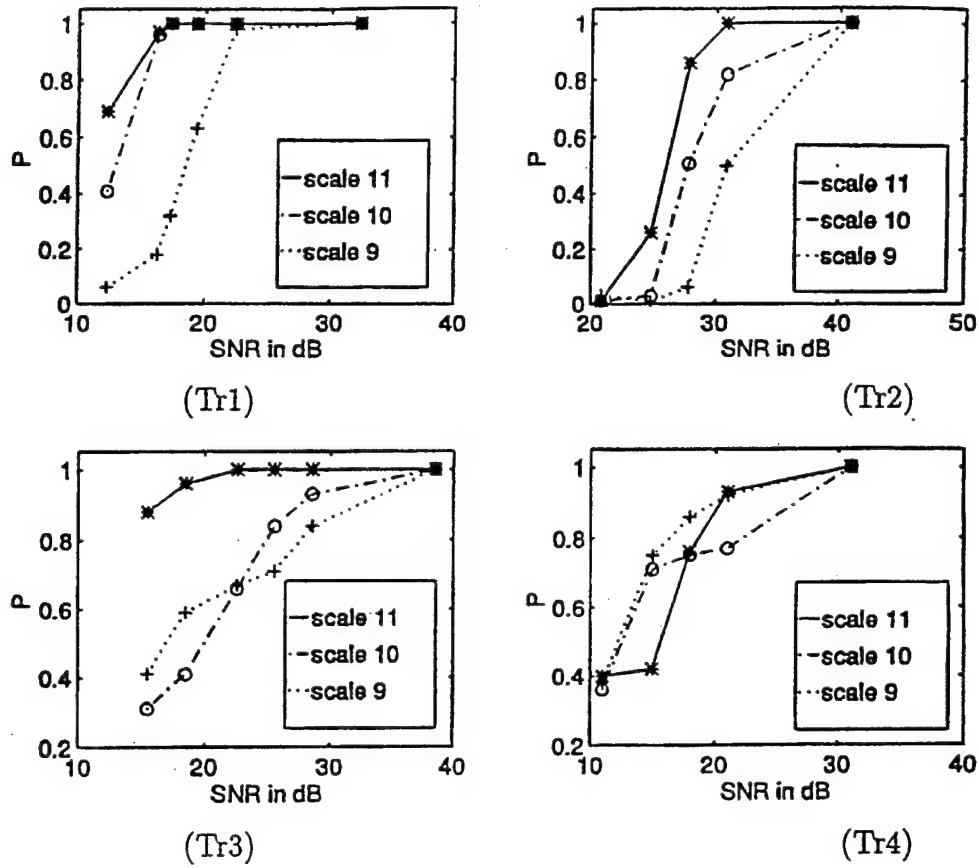
(Tr1)

(Tr2)

(Tr3)

(Tr4)

Figure 6. Probability of identification (P_I) of the signals
(a) P_I of signals from Transmitter 1 (b) P_I of signals from
Transmitter 2 (c) P_I of signals from Transmitter 3 (d) P_I of
signals from Transmitter 4.

V.   CONCLUSION

1.   CLASSIFICATION OF PUSH-TO-TALK COMMUNICATION

The main objective of this study is to determine a robust
wavelet based algorithm designed to extract features to identify

push-to-talk transmitters. Robustness, compact signal representation capability, and low computational complexity are the main advantages of the wavelet analysis, which is used in the feature extraction (identification).

Push-to-talk communication recordings provided for this research have a common feature: They all include a transition from the off-to-on state, as well as the on-to-off state. The turn-on transition phase is unique for each transmitter, and can effectively be used for classification purposes. The recordings differ from each other by the waveform in the length of the transition region. The feature for the classification of the signals is contained in the signal envelopes. The turn-on part of the envelope is a transient and, hence, a wideband signal. The original push-to-talk transmitter recordings are not in appropriate form for WT analysis. Thus, the recordings are pre-processed to be usable for WT processing. Differentiation of the envelope of the signals is used to transform the data into pulse-shaped transients. Filtering is applied to both the envelope and the differential to improve the signal-to-noise ratio.

A distance algorithm is introduced in this work. It is based on an Euclidean distance measure between the wavelet coefficients of two data set in terms of magnitude and relative position on a given scale. Decisions about the origin of the signal are made according to the distance measures between the signals and the templates, where each template represents a different transmitter. A small distance value implies that the signal belongs to the same set as that particular template. In its current form, the classification assumes that any signal of interest belongs to one of the four sets.

The distance algorithm was applied to four different signal

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sets. The first recording in any of the sets is designated to be the template. Instead of using all the wavelet coefficients, just the local extrema are used. Using only the local extrema reduces the computational complexity of the algorithm.

The distance measure between the signal and the templates is the sum of all Euclidean distances between paired peaks of the signal and the templates. It also includes a penalty factor due to the relative square root distance between the matched ranked pairs and their difference in amplitude. Matching signal peaks to the template is performed by ranking. Before pairing the peaks, the maximum peak of the signal is aligned with the maximum of the templates.This tends to reduce the penalty weight for like signals which are not aligned in time.

The distance algorithm described in chapter 4, the one that uses all the extrema and the pairing of ranked peaks allows robust identification of the signal sets. A printout for all programs is provided in Appendix B.

2.   RECOMMENDATION FOR FUTURE STUDY

The distance algorithm introduced in Chapter 4 gave promising results in classifying the four signal sets provided for this study. Three important issues have not been addressed in this research: i) the template selection, ii) a threshold technique, and iii) incorporation of information from other scales. In this work, templates are chosen arbitrarily from the signal sets. When the signals to be identified are from the four sets, the algorithm is capable of classifying the signals. However, if the signals do not belong to these sets, the algorithm will compute a distance to each of the templates, which could lead to misinterpretation hence misclassification.

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A thresholding technique and robust template selection should be the subject of further study.

Also, no attempt was made to combine information from several scales. Identification was obtained by using just one scale (i.e. highest frequency location). Typically, Scale 11 worked best. If the distance information from Scales 9 and 10 could be used, a potentially more robust identification performance should be realized.

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Appendix A

Appendix A consist of 2 sets of 4 figures (Figure A.1 - A.8). The first four figures use data at their original SNR value while the last four figures use data at an SNR level 10 dB below the original values. The absolute SNR levels of the originals are 32.38, 40.87, 38.58, and 31 dB for transmitters 1,2,3 and 4, respectively. Figure A.1 and A.5 use signals from transmitter 1. Figure A.2 and A.6 use signals from transmitter 2. Figure A.3 and A.7 use signals from transmitter 3. Figure A.4 and A.8 use signals from transmitter 4.

These figures allow easy determination of the maximum and minimum values as well as the mean and variability behavior of each test SNR level. One can fairly easily establish the sensitivity of each set relative to its template and to members of the other sets. The second set (Fig.A.5-A.8) provide a sense of the degradation of the identification procedure as the SNR is lowered by 10 dB. More information in terms of identification ability and SNR levels are provided in the main body (see Fig. 6).
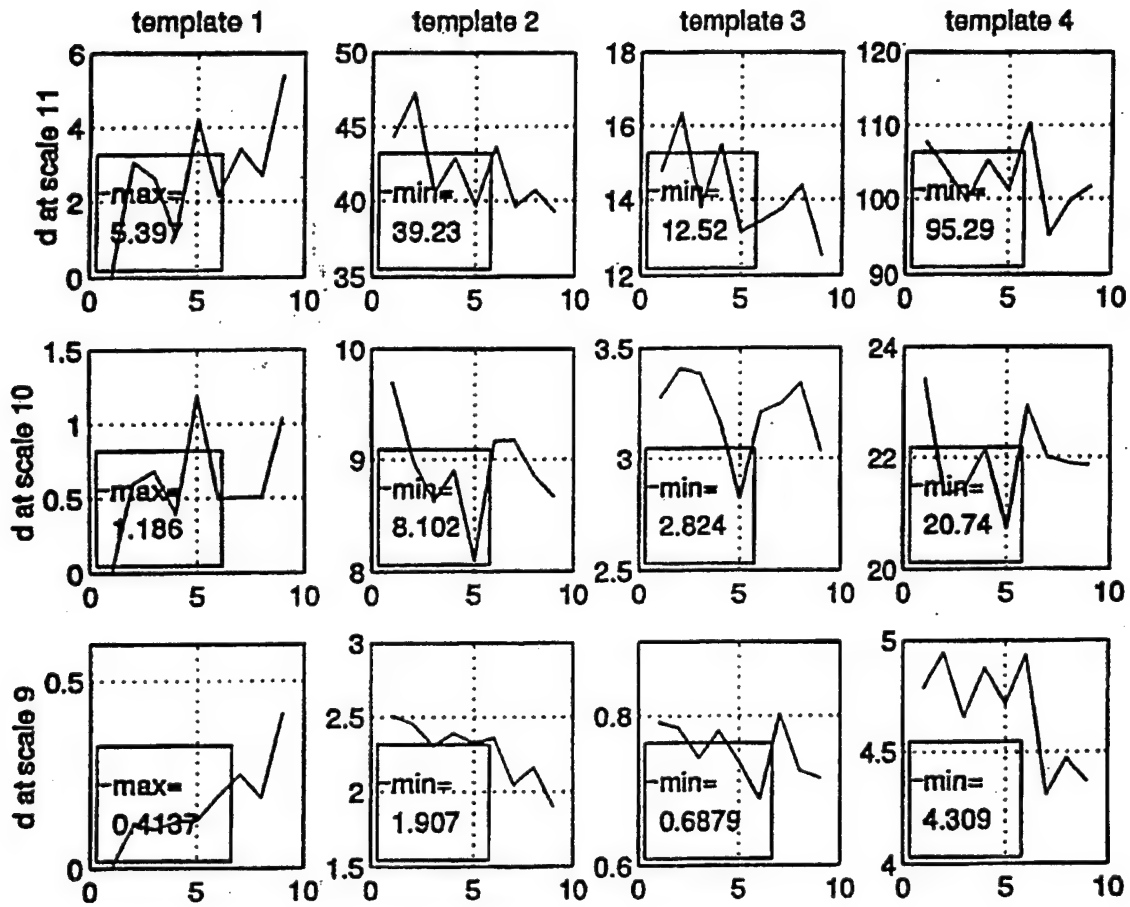
Figure A.1 Distance measures at the output of templates when signals from Transmitter 1 are the inputs. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
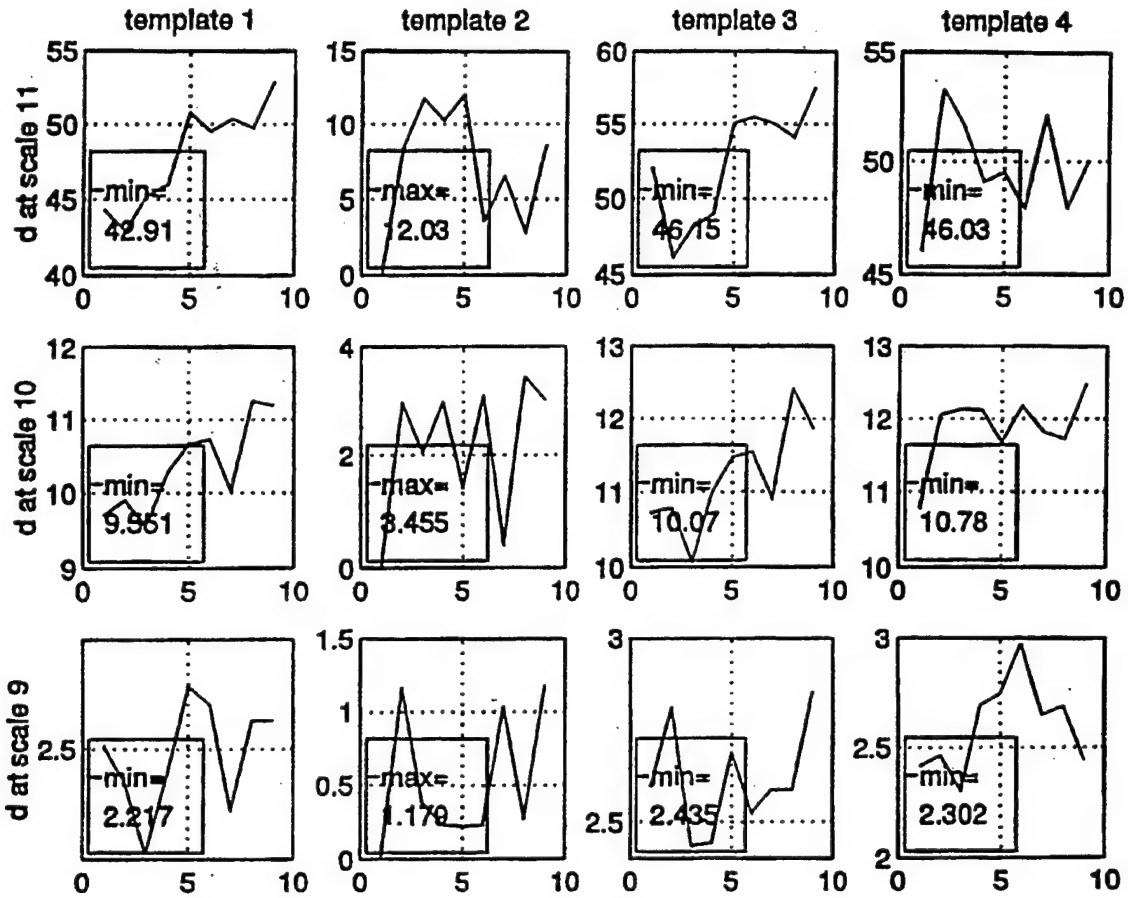
24

Figure A.2 Distance measures at the output of templates when signals from Transmitter 2 are the inputs. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
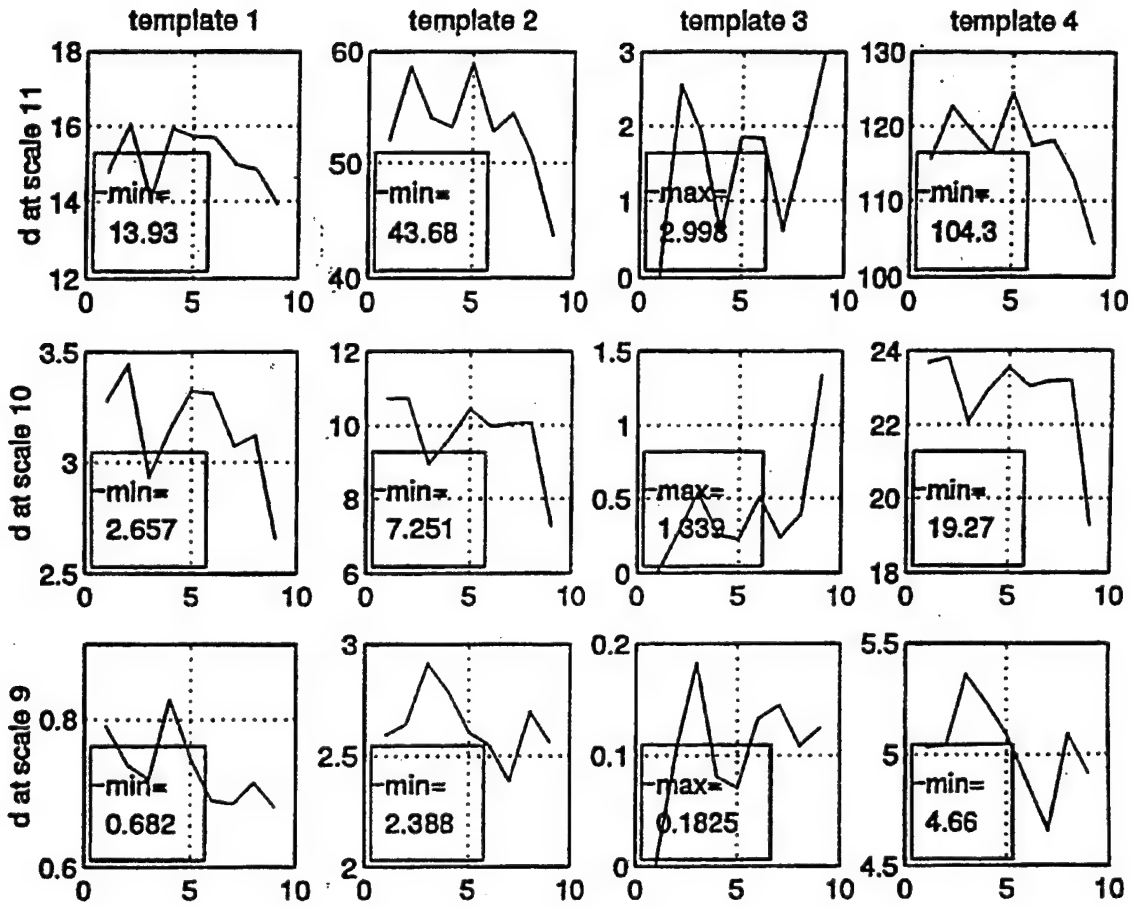
Figure A.3 Distance measures at the output of templates when signals from Transmitter 3 are the inputs. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
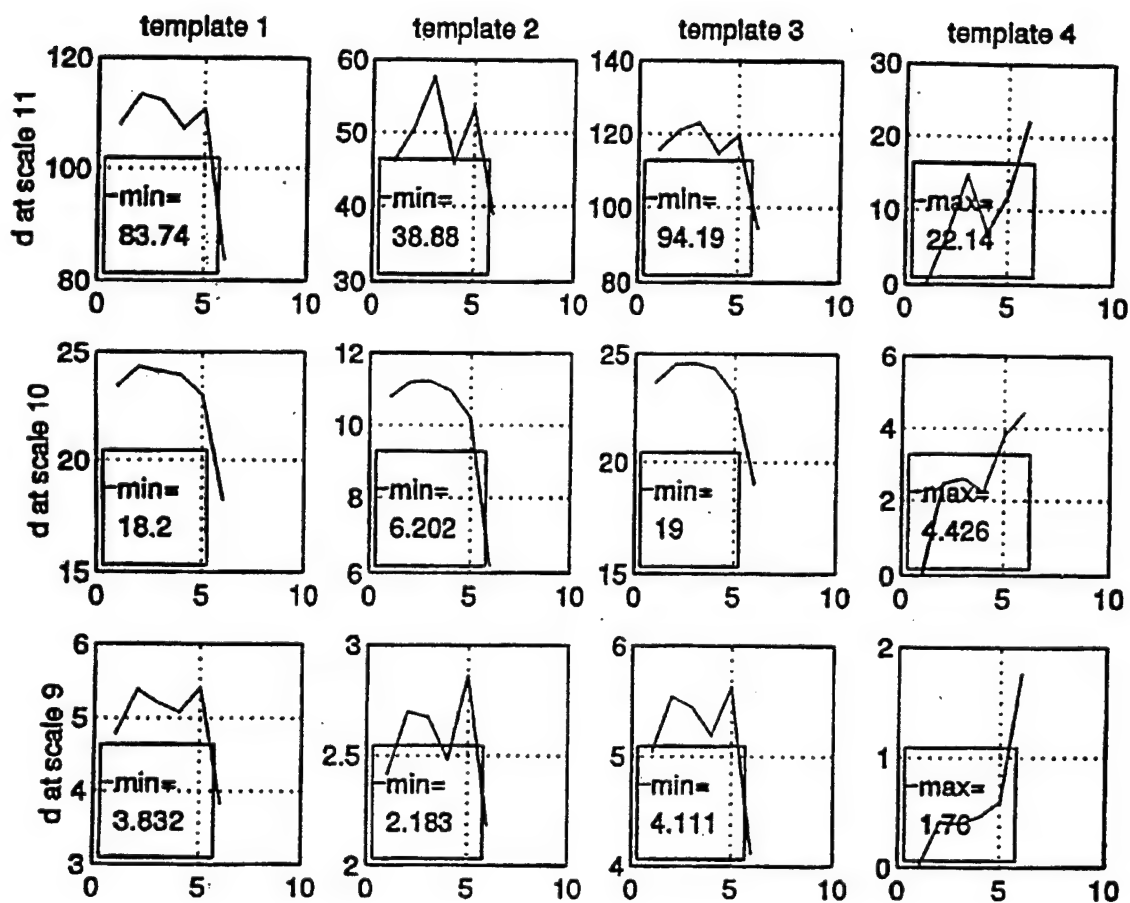
Figure A.4 Distance measures when signals from Transmitter 4 are the inputs. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
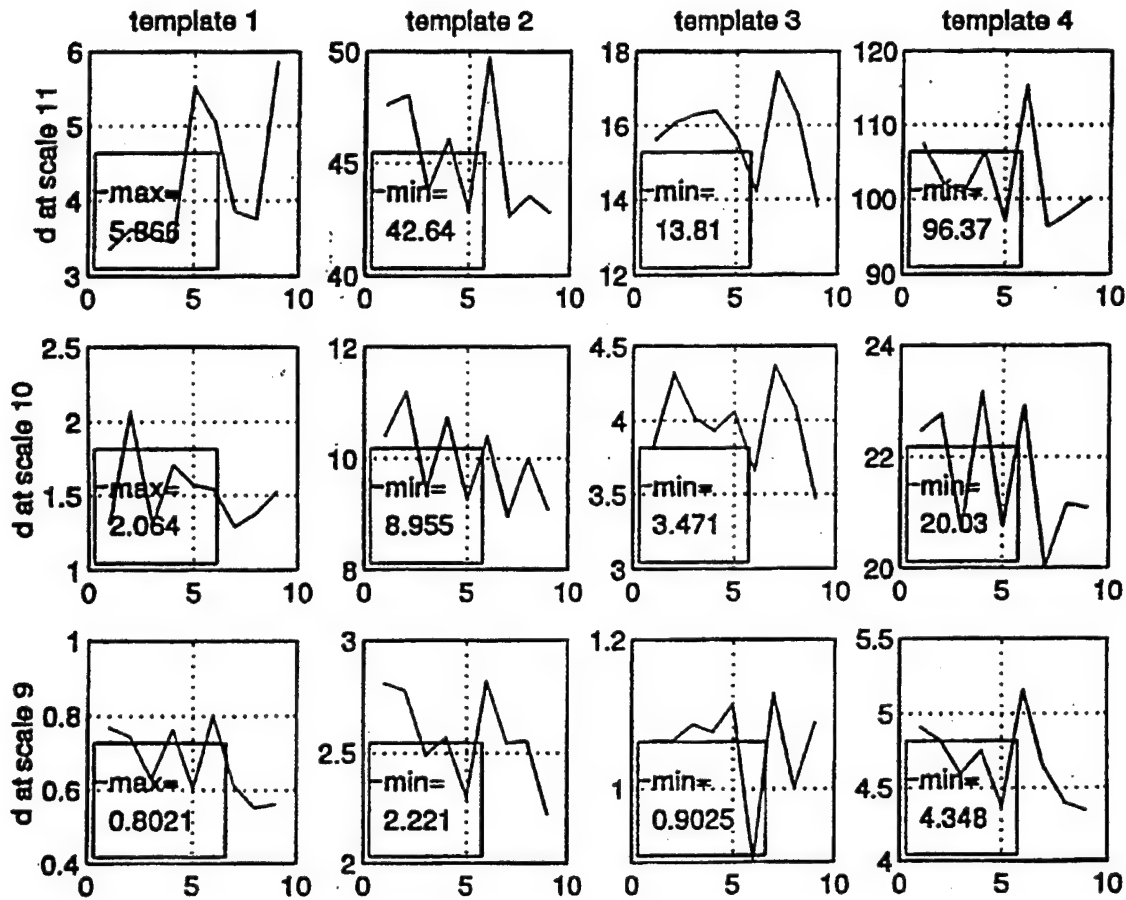
Figure A.5 Distance measures when signals from Transmitter 1 are inputs and their SNR values are 10 dB lower than the original data set. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.

Figure A.6　Distance measures when signals from Transmitter 2 are inputs and their SNR values are 10 dB lower than the original data set. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
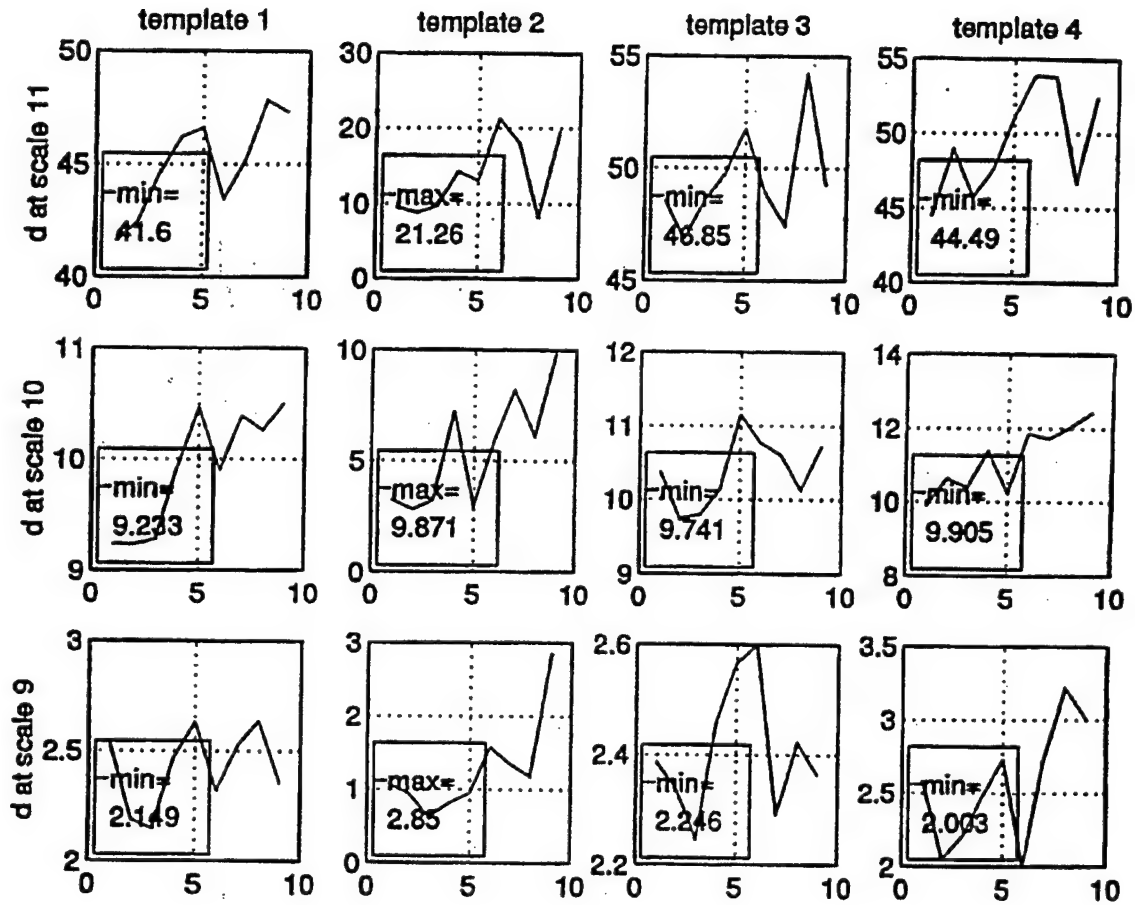
29
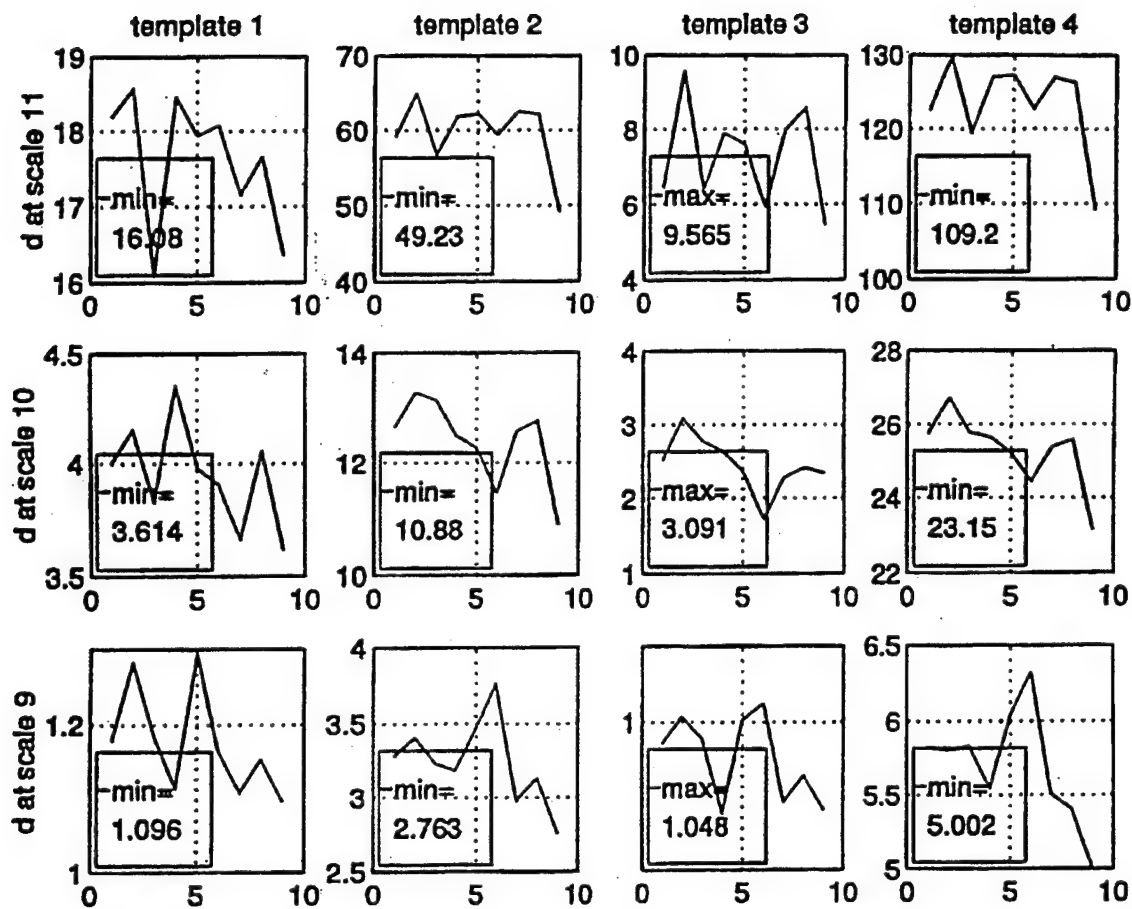
Figure A.7 Distance measures when signals from Transmitter 3 are inputs and their SNR values are 10 dB lower than the original data set. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.

Figure A.8 Distance measures when signals from Transmitter 4 are inputs and their SNR values are 10 dB lower than the original data set. Horizontal axis shows the number of the signals. Each column represents a template. First row is for Scale 11; second row is for Scale 10; third row is for Scale 9.
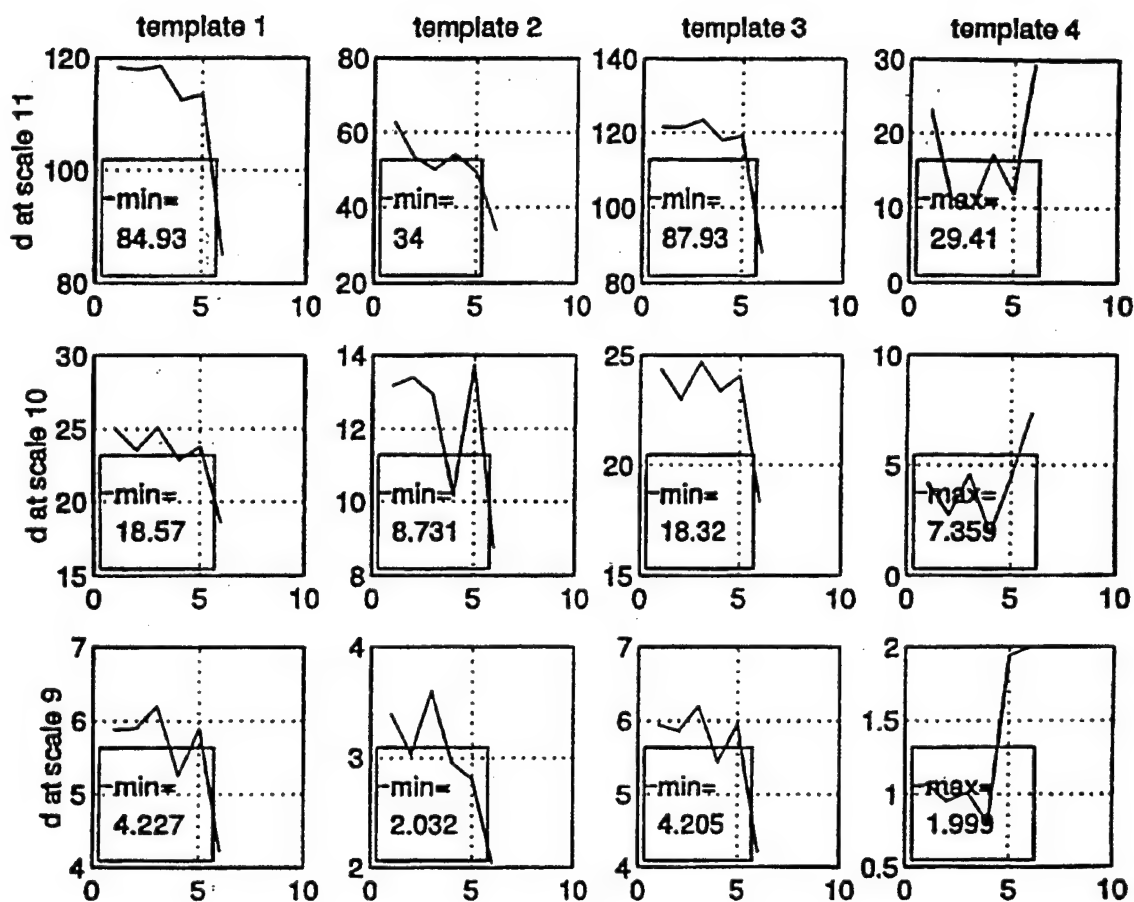
Appendix B

This appendix provides a listing of the Matlab code used to obtain the identification probabilities.

```
%                    WTSIGNAL.M

% This program removes  the  DC, takes the envelope, and filters
% the record of a transmitter. Then  it takes the
% differential and filters again to obtain a signal applicable to
% wavelet processing.

x=input(' enter the signal name ');%all programs assume a data
%     vector of length N, which is a power of 2
x=x-mean(x);  % removes DC component
y=envelope(x); % takes envelope
my=asmooth(y,100);% boxcar averaging size 100
dmy=diff(my);% differential of the envelope
mdmy=asmooth(dmy,50);%boxcar averaging size 50
% add on one data  point (zero) for the lost one in differentiatio
n
i=length(mdmy);
mdmy(i+1)=0;
clear x y my dmy i
end
```

```
function [y] = asmooth(x,L)
% boxcar averager of length L, creates as many data points
% (length of y) as the length of the input vector x.

y = [];
if nargin ~= 2,
     error('avsmooth: invalid number of input  arguments...');
end
if min(size(x)) ~= 1,
error('avsmooth: input argument must be a 1xN orNx1 vector');
end
x=x(:);
ns = length(x);
y=zeros(ns,1);

% average

%For the first L/2 points
for k=1:L/2
        y(k,1)=mean(x(1:L/2+k,1));
end

%for in the data
for k=L/2+1:ns-L/2
     y(k,1)=mean(x(k-L/2:k+L/2-1,1));
end

%for going  out  of the data
for k=ns-L/2+1:ns
        y(k,1)=mean(x(k-L/2:ns,1));
end
```

```
%              ENVELOPE.M

function [y,m] = envelope(x)
% computes the envelope by taking the absolute value of
% the Hilbert transform

y = [];
if nargin ~= 1,
     error('envelope: only one argument allowed');
end
if min(size(x)) ~= 1,
error('envelope: input argument must be a 1xN orNx1 vector');
end
x=x(:);
y=abs(hilbert(x));
```

```
%                    MAP.M

function   A = map(f,N)
% modified version of mapdn.m. It computes the amplitudes at the
% scale outputs.
M = length(f);
n = round(log(M)/log(2));
a = wavedn(f,N);
b(1) = a(1);b(2) = a(2);
for j = 1:n-1
  for k = 1:2^j
    index = 2^j+k+N/2-1;
    while index > 2^(j+1),index = index-2^j;end
    b(index) = a(2^j+k);
  end
end
a = b;
for j = 1:2^(n-1)
A(1,j) =a(1);
end
for j = 2:n+1
  for k = 1:2^(j-2)
    for m = 1:2^(n-j+1)
      A(j,(k-1)*2^(n-j+1)+m)  = a(2^(j-2)+k);
    end
  end
end
A=A;
```

```
%                    WAVEDN.M

function a = wavedn(f,N)
%
%
M = length(f);
n = round(log(M)/log(2));
c = dcoeffs(N);
clr = fliplr(c);
for j = 1:2:N-1 , clr(j) = -clr(j) ; end
a = f;
for k = n:-1:1
  m = 2^(k-1);
  x = [0]; y = [0];
  for i = 1:m
    for j = 1:N
      k(j) = 2*i-2+j;
      while k(j) > 2*m , k(j) = k(j)-2*m  ;end
    end
    z = a(k);
    [mr,nc] = size(z);
    if nc > 1 , z = z' ; end
    x(i) = c*z;
    y(i) = clr*z;
  end
  x = x/2 ; y = y/2 ;
  a(1:m) = x;
  a(m+1:2*m) = y;
end
```

```
%                    DCOEFFS.M

function c = dcoeffs(N)
%
nm = sqrt(2);
c = zeros(1,N);
if N == 2
c = [1 1];
end
if N == 4
c = [(1+sqrt(3))/4 (3+sqrt(3))/4 (3-sqrt(3))/4 (1-sqrt(3))/4];
end
if N == 6
q = sqrt(10);s = sqrt(5+2*q);
c = [(1+q+s)/16 (5+q+3*s)/16 (5-q+s)/8 (5-q-s)/8  (5+q-3*s)/16  (1
+q-s)/16];
end
if N == 8
c = [.3258030428051 ,1.010945715092 .892200138246,-.039575026236,
-.264507167369,.043616300475,.046503601071,-0.14986989330];
end
if N == 10
c = [.226418982583,.853943542705,1.024326944260,.195766961347,-.34
2656715382,-.045601131884,.109702658642,-.008826800109,-.017791870
102,.004717427938];
end
if N == 12
c = [.157742432003,.699503814075,1.062263759882,.445831322930,-.31
9986598891,-.183518064060,.137888092974,.038923209708,-.0446637483
31,.000783251152,.006756062363,-.001523533805];
end
if N == 14
c = [.110099430746,.560791283626,1.031148491636,.664372482211,-.20
3513822463,-.316835011281,.100846465010,.114003445160,-.0537824525
90,-.023439941565,.017749792379,.000607514996,-.002547904718,.0005
00226853];
end
if N == 16
c = [.076955622108,.442467247152,.955486150427,.827816532422,-.022
385735333,-.401658632782,.000668194093,.182076356847,-.02456390104
6,-.062350206651,.019772159296,.012368844819,-.006887719256,-.0005
54004548,.000955229711,-.000166137261];
```

```
end
if N == 18
c = [.053850349589,.344834303815,.855349064359,.929545714366,.1883
69549506,-.414751761802,-.136953549025,.210068342279,.043452675461
,-.095647264120,.000354892813,.031624165853,-.006679620227,-.00605
4960574,.002612967280,.000325814672,-.000356329759,.000055645514];
end
if N == 20
c = [.037717157593,.266122182794,.745575071487,.973628110734,.3976
37741770,-.353336201794,-.277109878720,.180127448534,.131602987102
,-.100966571196,-.041659248088,.046969814097,.005100436968,-.01517
9002335,.001973325365,.002817686590,-.000969947840,-.000164709006,
.000132354366,-.000018758416];
end
```

```
%               DISTANCE.M

% set up to work with 4 templates (i.e. 4 transmitters)
s1=input('enter the signal name');% wavelet transform output
kk1=input('enter WT matrix of template 1      :');
%mm1=input('enter WT matrix of template 2       :');
%tt1=input('enter WT matrix of template 3       :');
%vv1=input('enter WT matrix of template 4       :');

% assumes scales 6,7,8,9,10,11 are of interest
%(i.e. data length =4096 = 2^12 therefore  11 scales
%with only the last 6 of interest to this study
% scales 6 to 11 ; n=scale #; highest scale = highest freq band
for n=6:11
t=length(kk1(1,:))/(2^n);
col=n+2; % corresponding row for the scale
a=kk1(col,1:t:length(kk1(1,:)));
%b=mm1(col,1:t:length(mm1(1,:)));
%c=tt1(col,1:t:length(tt1(1,:)));
%f=vv1(col,1:t:length(vv1(1,:)));
s=s1(col,1:t:length(s1(1,:)));%  signal to be tested

% find local extrema
a=localext(a);
%b=localext(b);
%c=localext(c);
%f=localext(f);
d=localext(s);
%sort extrema in ascending order
[temp1,i]=sort(a);% template 1
%[temp2,j]=sort(b);% template 2
%[temp3,k]=sort(c);% template 3
%[temp4,q]=sort(f);% template 4
[x,m]=sort(d);

% Difference measures
shift1=m(length(x))-i(length(a));%shift for line up of max peaks
%shift2=m(length(x))-j(length(b));%shift for line up of max peaks
%shift3=m(length(x))-k(length(c));%shift for line up of max peaks
%shift4=m(length(x))-q(length(f));%shift for line up of max peaks
w1=[abs(m-i-shift1)];   %penalty weights
%w2=[abs(m-j-shift2)];    %penalty weights
```

```
%w3=[abs(m-k-shift3)];    %penalty weights
%w4=[abs(m-q-shift4)];    %penalty weights
w1(find(w1==0))=ones(1,length(find(w1==0)));%modific. for no 0
%w2(find(w2==0))=ones(1,length(find(w2==0)));%modific. for no 0
%w3(find(w3==0))=ones(1,length(find(w3==0)));%modific. for no 0
%w4(find(w4==0))=ones(1,length(find(w4==0)));%modific. for no 0
%  the smaller the distance d1, d2, etc. the more likely the test
%signal belongs to the transmiter 1,2 , etc.
d1(n)=sum(sqrt(w1.*(temp1-x).^2));
%d2(n)=sum(sqrt(w2.*(temp2-x).^2));
%d3(n)=sum(sqrt(w3.*(temp3-x).^2));
%d4(n)=sum(sqrt(w4.*(temp4-x).^2));
end
end
```

```
%                LOCALEXT.M

function [ou,k]=localext(sg)
% LOCALEXT extracts the local extrema of a vector
% nonextrema are set to zero
% [Y,K] =localext(x) will return the number of deleted samples
%-------------------------------------------------------------
%     copyright 1994 by Universidad  de Vigo
%     under GNU conditions
% Author: Sergio J. Garcia Galan
%     e-mail: Uvi_Wave@sc.uvigo.es
%-------------------------------------------------------------
l=length(sg);
sg=sg(:)';
ou=zeros(1,l);
ax=abs(sg);
MX=max(ax);
MX=MX+1;
ou(1)=sg(1);
ou(l)=sg(l);
k=0;
for i=2:l-1
if(sg(i)>sg(i-1))&(sg(i)>sg(i+1))
     ou(i)=sg(i);
     k=k+1;
     end
if(sg(i)<sg(i-1))&(sg(i)<sg(i+1))
     ou(i)=sg(i);
     k=k+1;
     end
end
k=l-k;
```

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